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Heart Patient Pathology Assessment using *ANFIS* with ECG & ECHO Information

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ABSTRACT:
There are many diagnostic procedures for cardiac pathology assessment today. ECG, Echo cardiography, Doppler Blood flow parameters, heart valve conditions, hypertrophy, X-ray image, angiogram etc. are some of these. In a continued assessment of a heart patient under long term observation with medication, some of the tests are repeated periodically to determine the prognosis, mainly the ECG and Echo. From these, it is required to assess the risk factor of the patient and determine if there is improvement or otherwise, so that the medication can be altered. Presently, this is based merely on the judgment of the cardiologist physician. Herein, a rather precise soft computing technique for correct assessment of the risk factor from these diagnostic tests is described. The use of Fuzzy logic based inferences are proven techniques even in many control and automation fields. Therefore, such a technique will be helpful in a precise determination of the health condition of the heart. The ANFIS is a combined Neural network cum fuzzy inference technique. It can deal with data from the ECG and its wave segments and the Echo Doppler information for this assessment.
Key words*:* Electrocardiography (ECG), Echocardiography, Medical Diagnostic Imaging, Fuzzy logic, Fuzzy Neural Networks, Takagi-Sugeno Model.

INTRODUCTION

The ECG patterns of a patient indicate, among others, what is known as myocardial infarction which is a major pathological problem. The width and amplitude of the Q wave in ECG is mainly considered as a criterion for such MI. The Q waves observed vary among the various leads because of the electrode orientation. It is felt that the width of the Q wave which is maximum among all the lead ECGs should be considered for assessment. The genesis of the Q wave is related to the time of propagation of the basic Action Potential (AP) waves in the myofibrils [1]. By a simultaneous plot of the several lead ECGs using electrodes on the chest from right to left, the peak of the Q waves are shifted in time among the several lead waveforms. This indicates the propagation time of the AP and in MI, the delay in propagation time at the infarct causes an increase in this propagation time. So, when we plot this Q wave maximal width along with the time of propagation from right to left in the heart, the following graph is obtained.

In the book "ECG and Ischemic Heart Disease: Clinical and imaging" [2], a table is given indicating how Q waves could be used for obtaining a grading of the pathology relating to MI.

These authors have indicated a 31 point scoring system using the Q waves in several leads. When the width of the Q wave is 10-15ms, they give one point; when it is more than 30 ms, they two points; when it is still more, three points are given. Thus, they give points for the Q wave in each of the 12 leads and sum them up to obtain a graded index for the severity of the pathology.

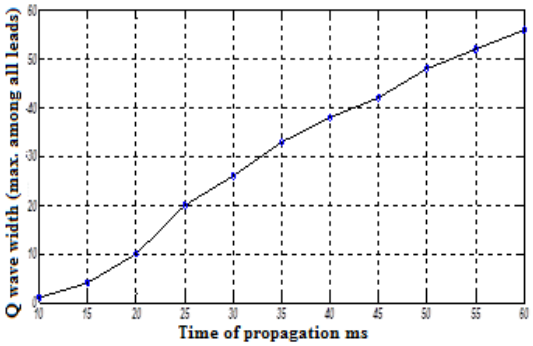

Figure 1. Graph showing approximate relation of Maximal Q wave width versus Propagation time measured value.

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

Thus a gradation of MI pathology is related through the Q waves. The Q waves are tiny segments in an ECG record and fine variations in the width and height of the Q wave are easily overlooked. But, we have shown [1] how the same can be directly inferred from the measurement of the AP propagation.

Earlier, before 1934, Q waves of more than 0.048 and 25% of R wave were considered pathological. The TIMI investigators (Thrombolysis in MI) classified Q as pathological if it is wider than 30ms based on Sylvester Criteria. Two more documents redefined it in 2000 and 2007.Today, the trend is to assess beforehand, immediately after a heart problem, the possibilities of an infarction and its location, size and so on. While the Q wave is a first indicator, time of propagation which can be conveniently measured with simultaneously observed ECG waves, is a more decisive indicator.

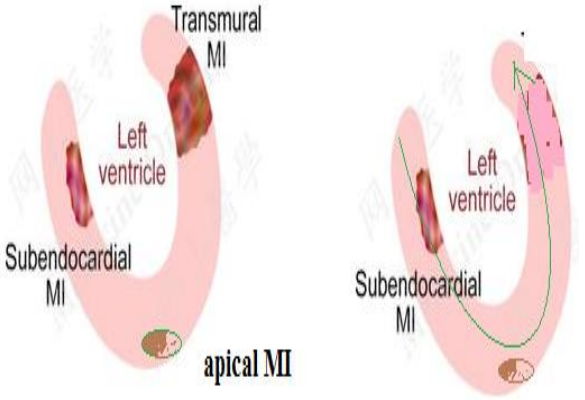

Figure2. Sub endocardial and apical infarctions do not generate Q wave because the path of APP is still available. Transmural infarctions do indicate a significant Q.

Some of these new concepts in adjudging the MI with or without Q waves is described in the book by Antoni Bayes de Luna in chapter 9 [2]. As shown in Figure 2, infarcts which are inside are sub-endocaridal. Those which are covering the entire through section, (though only a small length) are the ones that delay the conduction from right to left and cause increased time of AP propagation. Sub-endocardium infarctions do not generate a Q wave. Basal area of left ventricle also do not. The reason for the above is that the propagation of action potential is not affected by such apical or small sub-endocardial infarctions, because the wave can propagate in between where the tissue is good. We have shown that only if the APP time is increased, Q waves are generated.

But it is very useful to continuously monitor the critical patient with the monitor as well as the APP time. What happens in the time course of a heart attack (HA) is shown in the flow graph below.

Coronary Occlusion → (15 min) Formation
Cellular infarction → subendocardium → epicardium → transmural (Hours)

During this time course, there would be a progressive increase in the APP time from 20 to even 50ms. Thus, when it becomes transmural, the time delay to pass through the total cross section of the infarct is evidently more.

Cardiac MI research has utilized the CE and CMR imaging as well, though the procedures are permissible for patients who are not very critical or those who have survived a MI. The CMR (Cardiac Magnetic Resonance imaging) is able to quantify the size of infarction in the cross sections of the images. Injured tissue around an infarct scar results in the RSR' pattern of the QRS complex [3]. However, the diagnostic and prognostic values of these subtle abnormalities within the QRS complex were not clarified in prior studies. In 2006, Das et al, proved fragmented QRS complex in patients with coronary artery disease (CAD) was associated with myocardial conduction block due to myocardial scar detected by myocardial single photon emission tomography (SPECT). Fragmented QRS (fQRS) was defined by an additional R wave (R') or notching within the QRS complex. fQRS improved identification of prior myocardial infarction in patients who are being evaluated for CAD. Since that report, the usefulness of fQRS for the diagnosis and prediction of prognosis has expanded to patients with ischemic and non-ischemic cardiomyopathy and patients with primary cardiac diseases.

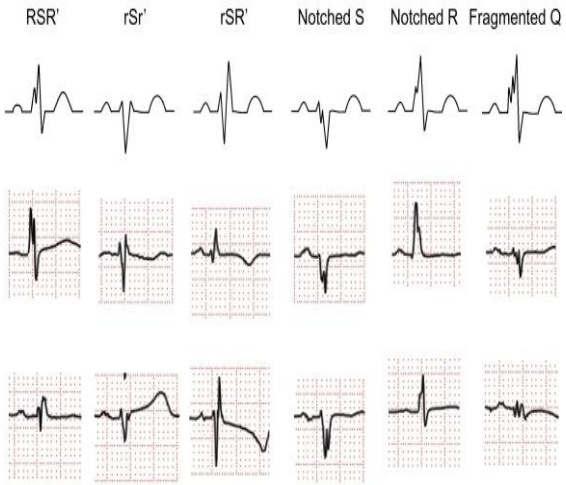

Figure3. Showing fragments QRS complex as associated with MI (Ind. Pacing Electro Physiol Journ, 2010).

As far as a grading index for MI pathology is concerned, such an fQRS is only causative to increase

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

the APP. Such notches in QRS are also, since long, been considered to be due to bundle branch block, but this author speaks of MI as contributive to such notches, which may due to the AP propagating through two different pathways with a time lag.

Sylvester Criterion

Sylvester [4] proposed a MI estimate scheme from QRS waves by combining waveform amplitude and timing with known pathological information about hypertrophy, bundle branch block and other criteria for abnormal heart functions as necessary.

When scoring, two concepts are considered: "weighting" and "selecting". "Weighting" refers to the number of points awarded for the criteria satisfied which is provided to the right of the criteria. If the point value is not listed directly to the right of the criterion, its point value is the same as the criterion directly above it. "Selecting" is the process of choosing a single criterion from a group. The groups are of course the usual LAFB, RBB, LVH etc. To determine the above groups in an ECG, they have given a flow chart. This is given for illustration of the method, for Lead 1 ECG alone below (Figure.4).

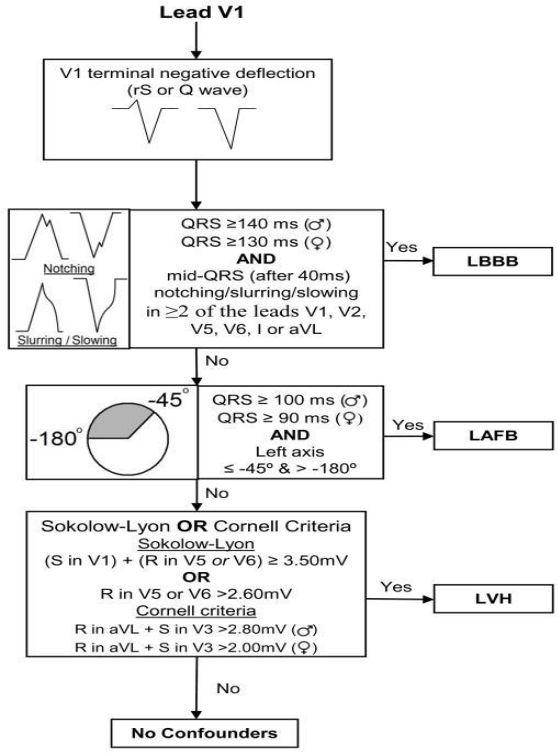

Figure. 4. Flow chart of Sylvester criterion for group pathology finding.

CARDIAC ECHO RESULTS AND EJECTION FRACTION

In cardiac investigations, which is concerned with patients with pathological hearts, myocardial infarction is the uppermost criterion which is being discussed widely. Attempts correlating ECG abnormalities and echo-cardio graphic data with myocardial infarct volume are just a few. K. Lindvall [5] has given an account of about 17 dead heart patients by autopsy of heart post mortem with their former ECG records. They report that that Echo mapping provides useful information of segmental LV wall function in MI.

From echo-cardiograph, several views of the heart and its chambers are provided. One important use of the echo image is to find the heart valve opening areas and to determine whether the valves are normal or thickened. Doppler shift due to blood flow velocity of the ultrasound received signal is used to find high velocity flows and regurgitation via valves, the mitral, tricuspid and aortic. M-mode or motion mode images can show the movements of the heart periphery so as to assess if the heart is compressing and expanding properly [6]. Further, they determine the images of the ventricular chambers by their area during diastole and systole. Thereby, the program in the ultrasound scanner machine is providing the valuable information about how far the heart is compressing and pushing blood. This important information is provided as the ratio of ejected volume to the dilated diastolic volume of the ventricular chambers – the ejection fraction.

Then, what quantitative information is presently available to assess ventricular pathology? Though not from the ECG, the Ultrasound echo cardiogram calculates a value called **"Ejection Fraction**" (EF), which is obtained from the ultrasound display of chamber volumes [5]. This EF value varies between 55-80% for normal heart functioning and will drop down with patients having Q waves. Q waves indicate damaged cardiac fibers and therefore reduce the compression action in those areas. Using M-mode echo image, it is evident that certain areas of the ventricle are 'akinetic' (not moving sufficiently). The Ejection fraction (EF) gets reduced on account of insufficient contraction of the ventricle. Figure 5 illustrates this EF.

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

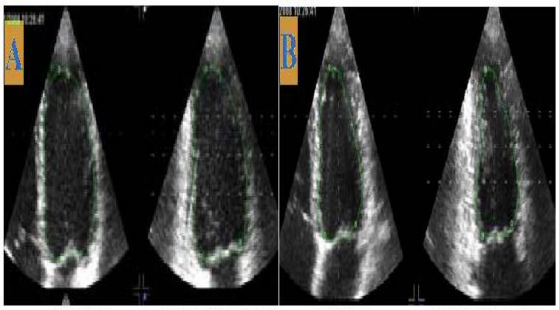

Figure 5. Illustration of Ejection Fraction relating to ventricular pathology.

Some work has been done for predicting if a patient will survive at least one year after a heart attack, using Echocardiogram data. Salzberg [7] of Harvard University Centre for Research in Computing Technology developed a program for this and their data set had the following attributes, among others: Age, Months alive, still alive or dead. The echo data included whether the Patient had pericardial effusion or not, wall motion of the left ventricle mentioned as a score of 1-5, left ventricular end diastolic linear dimension. At that time (1988), the Ultrasound machines were not developed with the software for a direct calculation of Ejection fraction of ventricle. Kan. G. Visser. C., Kooler. J. and Dunning. A [8] had used echo M mode wall movement scores to predict survival index of patients. The Ejection fraction of the ventricular volume is thus a vital parameter for the pathological heart.

Another factor usually measured in present Ultrasound machines is the "fractional Shortening', which is a measurement based estimate of the compression of the left ventricle. This ratio is usually 0.4-0.6 and its drop is well indicative of anything from ischemia to impending block and infarction.

In our attempt, we combine both ECG and Echo data in order to provide an index (or score) of the risk on the patient after a heart problem and to estimate thereby the urgency of suitable medication and surgical procedure.

DATA ANALYSIS OF Q WAVES FOR AN EXPERT FUZZY INTERFERENCE SYSTEM

Having discussed the several parameters which can be used for assessing MI grade, by using them, an index (or score) is to be arrived at.

1. Since the time of APP is includes the diagnosis by the Q wave width and height, if this time is measured along with the ECG, it can be used as one important input parameter for finding the MI grade score.
2. The presence of S-T segment complications, such as raised ST or depressed ST relate more the ischemic conditions with or without an infarction. This also should be included in the method of estimating the MI grade score.

ST segment depression seen in sub-endocardial ischemia (Figure.6) or infarction can take on different patterns: T wave inversion with or without ST segment depression (B) is sometimes seen but not ST segment elevation or Q wave.

In transmural pathology, ischemia in the subendocardium spreads to the epicardium and involves full thickness of the myocardium. In the acute phase, the ECG signs are ST segment elevation (Figure.7).

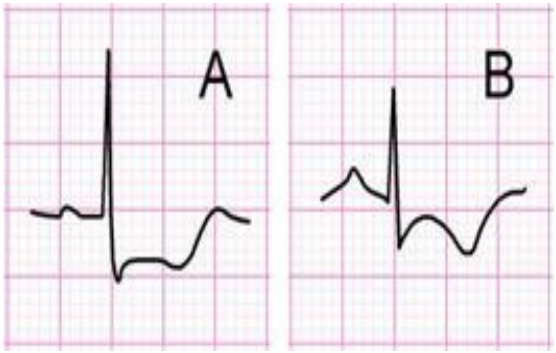

Figure 6. ST depression in subendocardial ischemia.

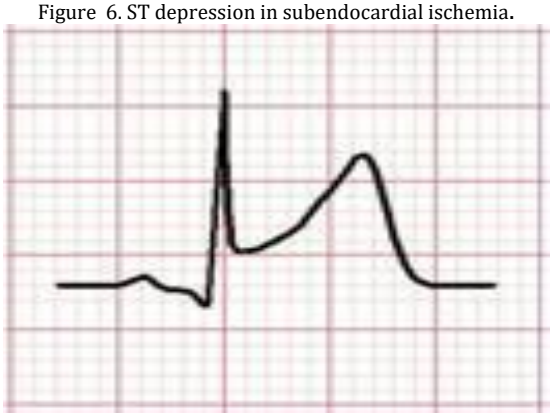
Figure 7. ST segment elevation due to transmural ischemia.

So far, the Sylvester criterion and other grading methods based on ECG have gained ground in diagnostic procedures, while Echo cardiograph results indicate the Ejection fraction. Normal heart ejection fraction is over 50%, while hearts with less than 35% are abnormal. However, ejection fraction being normal does not preclude a heart failure and that is the major concern in a diagnosis of an impending failure.

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

Heart failure has been traditionally viewed as a failure of contractile function and left ventricular (LV) ejection fraction (EF) has been widely used to define systolic function, assess prognosis, and select patients for therapeutic interventions. However, it is recognized that heart failure can occur in the presence of normal or near-normal EF: so-called 'heart failure with preserved EF (HF-PEF)'.

Conduction disturbances and arrhythmia are considered as suitable candidates for heart failure, even though the heart musculature is normal. The ejection fraction in these hearts may be fluctuating and can be low, high and in between. These could come under the category HF_PEF.

CHOICE OF THE VARIABLES FOR RISK ASSESSMENT

The modeling of such data with more inputs and values of the above parameters could be done with a Fuzzy model [9].There are two Fuzzy models in a Fuzzy logic based Inference System (FIS). The first method is called the Mamdani method and the second one as the Takagi-Sugeno Model.

We have to determine which parameters are input parameters and which is the expected output parameter.

The use of ANFIS (Adaptive Neuro Fuzzy Inference System) has been only recently only reported in cardiography literature. Negar Ziasabounachi and Iman Askerzadea in Turkey [10] had attempted the ANFIS technique for classification of general heart diseases, but not for the case of MI pathology. Ouyang et al, have used an artificial neural network for analyzing ECG with Q wave in V1 and V2 leads [11].

Among the several parameters for assessment, the Myocardial infarction size (rather, volume) is a very important one. But data relating the MI volume can seldom be obtained in sufficient quantity for verification. So, the MI volume cannot be taken as our output quantity in the modelling. What we need by our model would be the actual performance of the heart. Even with some segments of infracted tissue, the heart might be able to pump adequately. The ejection volume rather than the ejection fraction would be a good measure of this.

With any of these Fuzzy models, given the ECG parameters about the Q wave and ST segment, the time of AP propagation and the volume of the LV, Fractional shortening and ejection fractions, the relative functional behaviour of the ventricle can be obtained.

Therefore we have some antecedent parameters of the Fuzzy model and in each of the parameters, we have to define clinically significant linguistic variables.

The output decision parameter is similar to current diagnostic inferences which would mean one of the following:

1. Acute recent myocardial infarction
2. Moderate but recent myocardial infarction
3. Recent mild myocardial infarction
4. mild long standing infarction
5. moderate long standing infarction
6. Acute long standing infarction

Hence, it was found advisable to classify the output in two functions:

1. Acuteness of infarction
2. Whether it is recent (and hence recoverable) or old.

There are eight premise parameters each of which can be divided into three fuzzy membership functions, for three levels of classification – mild, moderate and large.

For the present, the mainly used parameters are listed below as 1 to 7. Q waves are supposed to be pathological if one or more of the following are noted from the ECG records.

1. 40 ms (1 mm) wide
2. 2 mm deep
3. 25% of depth of QRS complex
4. Presence of LAFB, RBB, LVH and other symptoms recognizable from the ECG.
5. Time of AP propagation.
6. LV volume and Ejection fraction
7. Fractional shortening

The Sylvester criterion, though showing various groups in the table for score calculation, it may be noted that there is no difference in the QRS based estimate among all but the LVH syndrome. Only for LVH, they say that Q wave width must be more than for other cases by 10 ms to score a point.

i. So, if the width of the Q wave is less than 20 ms it is low and 20-40 as moderate risk and over 30 up to 100 is considered as high risk.

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

ii. Likewise if the peak of the Q wave is 1 mm to 1.5 mm, it is considered as low risk; if 1.5 – 2.5 mm, it is moderate and more than 2 mm it is high risk.
iii. If the ratio of the Q peak to R wave is less than 20%, it is low risk; if between 15 to 40%, it is moderate and if more than that it is high risk.
iv. The presence of bundle branch block, notched QRS (fQRS) and LVH or hypertrophy are to be given fuzzy membership functions in a combined variable. This is based on pattern recognition of the QRS in the several leads. The gradation of fuzzy input would be based on small, significant and large amounts of such QRS abnormalities.
v. APP Time: The proposed AP Time of propagation is a very useful decisive factor which combines the information about infarction through the delay in time. This measurement is what is proposed here
vi. ST segment elevation is a critical factor in MI estimation. If the elevation is present right from the end of the S wave, it is high, and depending on its rise amplitude, we can estimate three levels: HIGH, MEDIUM and NORMAL.
vii. Ejected Output: The Left ventricular volume multiplied by the ejection fraction as reported from the Ultrasound machine is a good indicator of cardiac function. With considerable damaged tissue, the value of the ejection fraction drops. So, we can classify this LV ejection output into three fuzzy categories as LOW, MEDIUM and GOOD.
viii. Fractional Shortening has normal values of 10 to 40% and we can define three fuzzy memberships around this.

For an ANFIS model, Membership functions have to be Gaussian or bell shaped with two adjustable parameters to shape it. Coming to the output decision which is named as Risk value, we can divide into three categories initially as LOW, MODERATE and HIGH, though the remaining three pertaining to long standing can be considered as a separate output function which can be linguistically termed as not recent, fairly long standing and old.

The Takagi Sugeno model [9] suggests equations describing the output variable "RISK" *Rn* in terms of the membership values of the seven inputs WIDTH (w), Height of PEAK (h), Q/R ratio *r* etc. Thus, these equations for Risk R, one for each rule, will be of the form:

$$R_n = p_n w + q_n h + r_n r .... + z_n \qquad ...(Eqn.1)$$

The p, q, r are coefficients of multiplication and z is the static independent factor.

The Sugeno model is feasible for adaptive adjustment of the input member functions and the equation coefficients *p,q,r.*

Such a method is known as the Adaptive Network or Adaptive Neural Fuzzy Inference System (ANFIS) [12]. The Model of the network is as shown in Figure8.

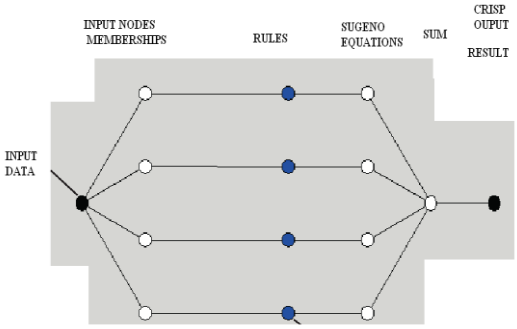

Figure8. An ANFIS network uses input data and output result and finds the Fuzzy Inference System model for such data pair. One single input and one output model shown.

Like a neural network, the method trains the output data with respect to input data, given a sufficient set of data points. The rule base given by the expert system is used. The training requires several iterations involving adjustment of the consequent parameters of p_n, q_n *and* s_n as well as the premise parameters of choice of Membership functions – their span. If Gaussian curve type of Membership functions are chosen, it adjusts the parameter σ of the curve. The training uses a hybrid algorithm of least squares and gradient descent methods. MATLAB uses such an algorithm.

We have used MATLAB's toolbox commands for generating the Fuzzy inference system and the ANFIS model generation. For this, we have taken case studies of cardiac patients suffering from Ischemia, infarction and hypertrophy. Though our number is small, it serves to illustrate the method by which our prediction of risk value can be of use in prognosis.

DATA SET SELECTION AND INFERENCE IN ANFIS MODEL

The data set for each patient can have many variables. These have been written down.

1. Width of Q wave mid-section
2. Depth of q wave (>2 mm deep)
3. R/Q ratio (>25% of depth of QRS complex)

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

4. Presence of LAFB, RBB, LVH and other symptoms recognizable from the ECG.
5. Time of AP propagation.
6. LV volume and Ejection fraction
7. ST segment rise
8. Fractional Shortening

If the above are the input parameters, the result parameter which is related to the above should be the so-called "risk factor" for the patient. Usually, the Physician and Surgeon decide the same after performing additional diagnostic tests. This includes angiography to detect an early blood clot or block in one of the coronary arteries. Motion mode Echo-cardiography can indicate a-kinetic (not moving) wall areas on the ventricle. In very rare cases, a CMR image of the heart can be done, but it is very troublesome to the patient. That would show the regions of infarction. The amount of infarction of tissue can be given as an indication of the severity or otherwise or the heart pathology. The risk factor of the patient's pathology as regards his heart condition is required even when the patient has to undergo some other minor surgical procedures other than on the heart itself, such as Hernia, Hydroceles etc. This risk factor has to be determined by the Doctor as an expert.

We took samples of data from heart patients with the above parameters and also acquired the estimated expert risk factor value for them.

Thus, the data set of each patient is 8. Having acquired sufficient number of data, we did the program for developing the ANFIS which would be a guide for heart patient evaluation, in general.

With more and more data on Q waves, echo data and Risk factor getting included, the better will be adapted network and the FIS for the benefit of the

Collecting such data from records, it has been feasible to develop the ANFIS trained network for clearly modeling the cardiac pathology and providing a crisp output in the form an index of MI value which might provide a comparable estimate of cardiac pathological diagnosis and follow up of their conditions with time.

THE GENERATION OF AN ANFIS MODEL

The following is the format for the data set preparation. In this we need not normalize the values of the data, because the ANFIS will choose the minimum and maximum of the data set as the range. The following data are entered in MATLAB for patients (eight shown). The last entry is the RISK factor as assessed by the specialist cardiologist.

```
hfdata(1)=[40 1.2 100 65 2.87 50 80]
hfdata(1,:)=[40 1.2 100 65 2.87 50 80]
hfdata(2,:) =[30 1  8  35 2.4 50 60]
hfdata(3,:) =[35 1.4  2  45 3.2  100  75]
hfdata(4.:) = [20 0.5  0.5  65 2.5 0 25]
hfdata(4.:) = [20 0.5  0.5  65 2.5 0.0 25]
hfdata(4,:) = [20 0.5  0.5  65 2.5 0.0 25]
hfdata(5,:) = [25  2  5  45  2.0 50  70]
hfdata(6,:) = [50  1.5 10  30  2.5 100 90]
hfdata(7,:) = [45  1.5  5  60  2.4  40  65]
hfdata(8,:) = [30  1.4  10 55 2.5  100  70]
hfdata(9,:) = [15  0.5  1  70  2.8  0  20]
hfdata(10,:) = [55  1.4  10  55  2.5  50  50]
```

It is noteworthy that the data is having seven values of inputs and one value of estimated output. The FIS is developed to match the data input and the output.

The following command is what is required to perform the ANFIS calculations by iterative neural network processing.

```
[fis er]=anfis(hfdata)
```

The MATLAB output is as under:

```
ANFIS info:
        Number of nodes: 161
        Number of linear parameters: 448
        Number of nonlinear parameters: 36
        Total number of parameters: 484
        Number of training data pairs: 10
        Number of checking data pairs: 0
        Number of fuzzy rules: 64
Warning: number of data is smaller than number of
modifiable parameters
Start training ANFIS...
  1       3.83824e-005
  2       2.42798e-005
  3       3.15093e-005
  4       2.93073e-005
  5       2.38005e-005
  6       3.22769e-005
  7       2.33455e-005
  8       1.68921e-005
  9       2.93543e-005
 10       2.82433e-005

Designated epoch number reached --> ANFIS
training completed at epoch 10.
fis =
        name: 'anfis'
        type: 'sugeno'
   andMethod: 'prod'
```

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

```
      orMethod: 'max'
   defuzzMethod: 'wtaver'
     impMethod: 'prod'
     aggMethod: 'max'
         input: [1x6 struct]
        output: [1x1 struct]
          rule: [1x64 struct]
er =
  1.0e-004 *
    0.3838
    0.2428
    0.3151
    0.2931
    0.2380
    0.3228
    0.2335
    0.1689
    0.2935
    0.2824
```

Then, in order to find out the actual inner model details. For this, we invoke the GUI command for Fuzzy inference system.

>>fuzzy

Now the GUI is opened and we can view the Sugeno functions and the Rules.

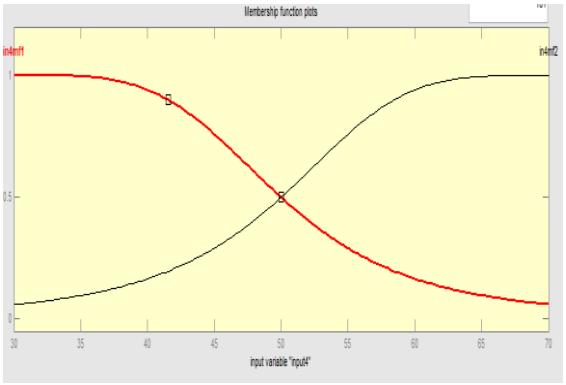

Figure 9. The membership functions are just two for each of the seven variables.

The ranges of the variables are:

anfis2.input.range

ans = 15 55 "range of Q wave width"

ans = 0.5000 2.0000 "range of Q wave height"

ans = 0.5000 100.0000 "ratio of Q to R"

ans = 30 70 "ejection fraction range"

ans = 2.0000 3.2000 "L. Ventricle lin. dimension"

ans = 0 100 "ST segment rise starting instant"

The output range is from 20 to 90 giving the risk factor.

The 64 membership functions are defined simply as Input1output1…. To input6output64

The Sugeno Rule Equation coefficients

There are 64 equations involving the 6 inputs x1, x2….x6 in the form, with seven coefficients.

P1x1+p2x2+p3x3+p4x4+p5x5+p6x6=p7y

For this if we type on command line

>>anfis2.output.mf.params

We get the coefficients as below.

ans 1 = 0.5705 0.0199 0.1483 0.6931 0.0458 0.9444 0.0192

ans 2 = 0.5877 0.0207 0.1539 0.7042 0.0469 1.0206 0.0196

ans 3= 0.1455 0.0049 0.0377 0.1827 0.0120 0.2448 0.0049

ans 4= 0.2598 0.0096 0.0464 0.3206 0.0221 0.5841 0.0081

ans 5= 0.1850 0.0063 0.0276 0.3746 0.0165 0.1663 0.0067

ans 6 = 0.1219 0.0050 0.0323 0.1884 0.0097 0.2469 0.0040

ans 7= 0.0848 0.0027 0.0248 0.2491 0.0104 0.0520 0.0039

ans 8 = 0.0846 0.0034 0.0287 0.1290 0.0075 0.2118 0.0026

ans 9= 0.0473 0.0016 0.0183 0.0582 0.0038 0.0774 0.0016

ans 10= 0.0488 0.0017 0.0188 0.0595 0.0039 0.0836 0.0016

ans 11 = 0.0229 0.0007 0.0320 0.0328 0.0018 0.0335 0.0007

ans 12= 0.0302 0.0010 0.0326 0.0417 0.0024 0.0553 0.0009

ans 13= 0.0399 0.0013 0.0703 0.0688 0.0031 0.0464 0.0011

ans14= 0.0365 0.0012 0.0709 0.0587 0.0027 0.0538 0.0010

ans 15= 0.1251 0.0038 0.3011 0.2100 0.0092 0.1534 0.0032

ans 16= 0.1255 0.0038 0.3014 0.2035 0.0091 0.1644 0.0032

ans 17= 0.4532 0.0280 0.0968 0.7131 0.0355 0.8269 0.0166

ans 18= 0.4979 0.0299 0.1092 0.7612 0.0391 0.9877 0.0179

ans 19= 0.0695 0.0031 0.0147 0.0952 0.0056 0.1334 0.0023

ans 20 = 0.2978 0.0122 0.0323 0.3846 0.0261 0.7914 0.0088

ans 21= 0.3417 0.0166 0.0502 0.5239 0.0221 0.4389 0.0099

ans 22= 0.2741 0.0153 0.0570 0.4575 0.0204 0.5499 0.0091

ans 23= 0.0688 0.0027 0.0191 0.1086 0.0047 0.0831 0.0019

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

ans 24= 0.1423 0.0061 0.0294 0.2091 0.0122 0.3788 0.0043
ans 25= 0.0347 0.0021 0.0117 0.0543 0.0027 0.0623 0.0013
ans 26= 0.0386 0.0022 0.0127 0.0585 0.0030 0.0755 0.0014
ans 27= 0.0130 0.0005 0.0211 0.0198 0.0010 0.0195 0.0004
ans 28= 0.0278 0.0011 0.0223 0.0385 0.0023 0.0620 0.0008
ans 29= 0.0423 0.0017 0.0504 0.0668 0.0029 0.0541 0.0012
ans 30= 0.0386 0.0017 0.0512 0.0641 0.0028 0.0652 0.0011
ans 31= 0.0868 0.0027 0.2069 0.1409 0.0062 0.1085 0.0022
ans 32= 0.0918 0.0029 0.2078 0.1481 0.0067 0.1289 0.0023
ans 33= 0.1754 0.0070 0.0446 0.2388 0.0159 0.3255 0.0067
ans 34= 0.2461 0.0091 0.0624 0.2583 0.0198 0.5301 0.0082
ans 35= 0.0285 0.0014 0.0114 0.0467 0.0036 0.0812 0.0015
ans 36= 0.1747 0.0069 0.0263 0.2034 0.0155 0.4833 0.0053
ans 37= 0.1767 0.0085 0.0098 0.3530 0.0131 0.1669 0.0057
ans 38= -0.0600 0.0008 -0.0128 0.0288 0.0005 0.0044 0.0004
ans 39= 0.0033 0.0012 0.0350 0.0657 0.0022 0.0136 0.0009
ans 40= -0.0122 0.0010 0.0328 0.0351 0.0028 0.1024 0.0008
ans 41= 0.0192 0.0007 0.0206 0.0283 0.0017 0.0330 0.0007
ans 42= 0.0258 0.0009 0.0222 0.0307 0.0020 0.0507 0.0008
ans 43= 0.0320 0.0010 0.0767 0.0523 0.0024 0.0436 0.0009
ans 44= 0.0421 0.0014 0.0778 0.0627 0.0032 0.0709 0.0011
ans 45= 0.0789 0.0026 0.1784 0.1358 0.0058 0.0967 0.0021
ans 46= 0.0626 0.0021 0.1769 0.1137 0.0050 0.0861 0.0017
ans 47= 0.3109 0.0094 0.7842 0.5107 0.0225 0.3900 0.0078
ans 48= 0.3096 0.0094 0.7840 0.5084 0.0225 0.3957 0.0078
ans 49= 0.1379 0.0087 0.0139 0.2621 0.0120 0.2393 0.0055
ans 50= 0.3413 0.0146 0.0659 0.3056 0.0226 0.8209 0.0095
ans 51= -0.0033 0.0009 -0.0023 0.0228 0.0016 0.0450 0.0006
ans 52= 0.3165 0.0125 0.0351 0.3393 0.0263 0.9072 0.0088
ans 53= 0.8360 0.0336 0.0589 1.3303 0.0502 0.7617 0.0215
ans 54= 0.1126 0.0098 -0.0147 0.3635 0.0125 0.2098 0.0057
ans 55= 0.0997 0.0055 0.0224 0.2279 0.0080 0.1018 0.0034
ans 56= 0.0092 0.0031 0.0111 0.1023 0.0065 0.2154 0.0020
ans 57= 0.0115 0.0007 0.0124 0.0232 0.0011 0.0208 0.0005
ans 58= 0.0308 0.0012 0.0171 0.0293 0.0021 0.0716 0.0008
ans 59= 0.0192 0.0007 0.0518 0.0340 0.0015 0.0280 0.0005
ans 60= 0.0422 0.0015 0.0547 0.0555 0.0032 0.0883 0.0011
ans 61= 0.0981 0.0036 0.1251 0.1634 0.0066 0.1061 0.0026
ans 62= 0.0480 0.0019 0.1201 0.0965 0.0040 0.0692 0.0015
ans 63= 0.2177 0.0067 0.5381 0.3610 0.0158 0.2719 0.005
ans 64= 0.2110 0.0065 0.5374 0.3517 0.0156 0.2789 0.0054

The graph of output risk factor versus all variables cannot be plotted because it is a hyper surface of 7 dimensions. To illustrate in a simpler way, using the parameters 1, 2 only, the plot is given as a surface plot by the GUI as shown below (Figure.9). The inputs are Q wave width and height.

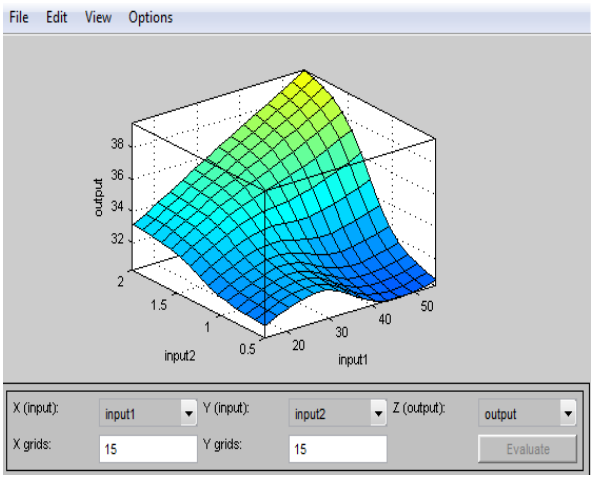

Figure 10. Showing output Risk factor Vs. Q wave params (only).

The neural network connecting the FIS inputs to the output as planned by ANFIS2 is shown below.

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

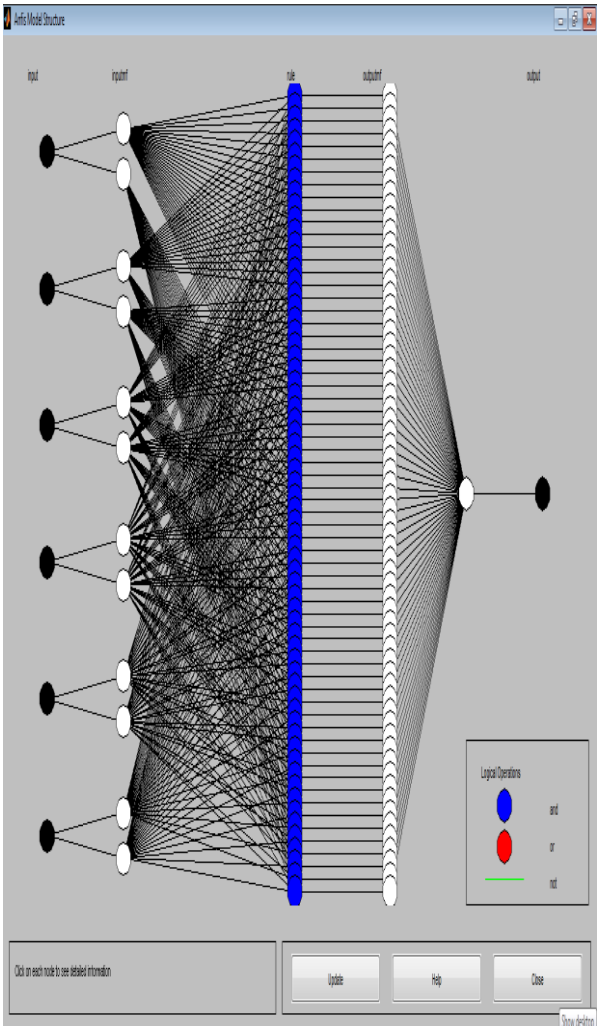

Figure11 .Showing the ANFIS Structure for the model with 2 MFs for all inputs and 64 rules.

To calculate for a typical patient with the data set [30, 1, 1, 35, 2.4, 70], the evalfis function is again useful.
Evalfis ([30, 1, 1, 35, 2.4, 70], anfis2)
ans = 78.0692

Indicating that this is the case of a high risk patient.
A word of caution: The number of data set used for forming the ANFIS cannot guarantee that a real expert system has been developed. That would in fact need a continuous observation of data over a large population from several hospitals. Unfortunately, data available in the *www* does not have both ECG and ECHO parameters to this extent.
ANFIS with 3 Membership Functions for each Input

The above was an ANFIS structure with just 2 membership functions, which is the default number in the ANFIS function without additional arguments.

In our case, we need to represent each of the variables with at least three membership functions. We add one more input variable as the 7th input: Whether the patient is having any of the following in ECG: RBB or LBB or LVH.

This variable is a two valued function of 0, 1 and fuzzified with just two membership functions.
All the rest are having three MFs (Figure.12a).

Accordingly, the Heart function_data becomes, for a data set of some observed patients:

```
   hfdata = 40.0000   1.2000  100.0000   65.0000
2.8700  50.0000       0    80.0000
    30.0000   1.0000   8.0000  35.0000   2.4000
50.0000   1.0000  85.0000
    35.0000   1.4000   2.0000  45.0000   3.2000
100.0000   1.0000  90.0000
    20.0000   0.5000   0.5000  65.0000   2.5000
0       0        25.0000
    25.0000   2.0000   5.0000  45.0000   2.0000
50.0000       0    70.0000
    50.0000   1.5000  10.0000  30.0000   2.5000
100.0000   1.0000  00.0000
    45.0000   1.5000   5.0000  60.0000   2.4000
40.0000   1.0000  75.0000
    30.0000   1.4000  10.0000  55.0000   2.5000
100.0000       0    70.0000
    15.0000   0.5000   1.0000  70.0000   2.8000
0     1.0000   40.0000
    55.0000   1.4000  10.0000  55.0000   2.5000
50.0000       0    50.0000
```

The range of input variables is got from the test data itself by the ANFIS program:

```
ans =   15   55
   0.5000   2.0000
   0.5000 100.0000
   30   70
   2.0000   3.2000
    0  100
         0        1
```

The membership functions for all but the last variable (RBB/LBB/LVH) have three Gaussians. The same is shown in Figure.12a.

The ANFIS Sugeno equations formed are found from the MATLAB structure for this ANFIS. The output Sugeno equations can be printed out by the command fis4.output.mf.params
Since they are too many, they are not given here.

ISSN: 0976 – 2965
IJBET (2017), 6(1):1-12

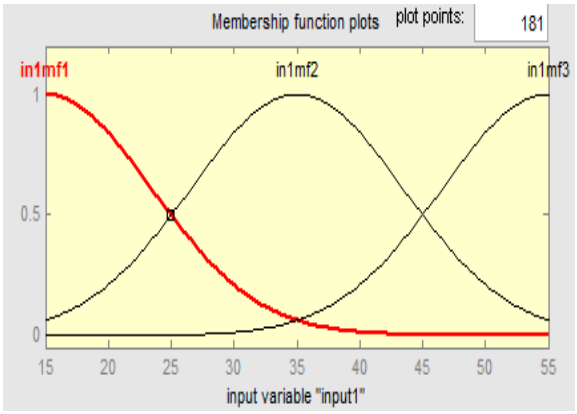

Figure 12a. MFs for all the six variables are three, Gaussian type. Only the one for first variable is shown.

The seventh variable has just membership functions, because mostly the information is "yes/no".

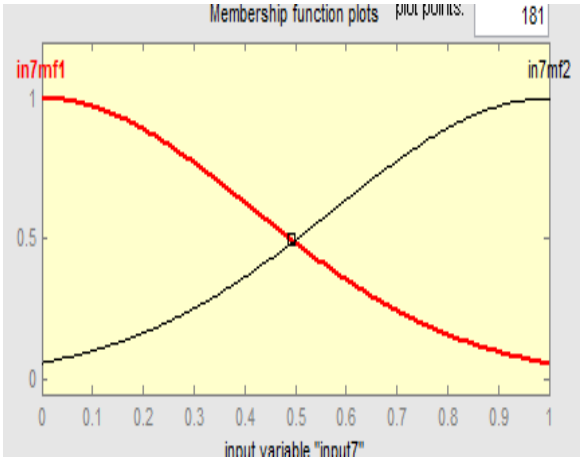

Figure 12b.MF for the variable 7 which is RBB/LBB/LVH.

Determination of Prognosis Indications

Using the developed ANFIS, any patient with these parameters can be evaluated for his risk factor.

As an example, the patient no.2 listed in Appendix had the parameters:

Q-width =35 ms
Q height = 1 mm
Q/R = 0.5
Ejection fraction =35
LV dim=2.4
ST rise point is at 50 percent of ST interval

The patient has RBB as seen in the notched QRS
To evaluate the above, we use the *evalfis* command after having developed the ANFIS network with test data.Fis4 is the name of the network.

evalfis ([35 1 0.5 35 2.4 50 1],fis4)
88.5843

As against the above patient's data, if the Q wave width reduces to 25 ms, let us evaluate what improvement in the heart's condition is noteworthy.

evalfis ([25 1 0.5 35 2.4 50 1],fis5)
55.8644

There is a considerable reduction of 33 % in risk value for the Q wave width reduction. If the ST segment rise is also improved, let us see how much more the risk reduces.

For that, let us assume that the ST rise starts at 30% from the T wave peak along the ST interval.For this data, we get
evalfis ([25 1 0.5 35 2.4 30 1], fis5)
31.9361
which gives a further improvement by 24%.

CONCLUSION

This shows how the ANFIS model is useful in assessing the improvements in a follow up of the patient. It is no doubt applicable for any heart patient. The authors have studied the genesis of Q wave pathology and examined many patients and also old records to arrive at their fuzzy inferences with respect to the ECG Q waves [13]. This expert modeling with ANFIS is much more useful than partial inferences based on limited diagnostic methods as in [14,15], since all diagnostic data are converged into the Fuzzy inference system with specialist expert ratings and we have given how the prognosis improvements can be subtly assessed.

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